

**Assignment Cover Sheet**

**Pattern Recognition & Machine Learning UG+PG 11482, 11512**

*You must keep a photocopy or electronic copy of your assignment.*

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| Student ID: | U3284513 | Unit/Subject Code: | 11482 | |
| Assignment No.: | 1B | Number of pages: (including this cover sheet) | |  |
| Date and Time Due: | | 29th of August, 23:59pm | | |
| Date and Time Submitted: | |  | | |

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Signed: \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_ Date: 23/08/2025

# INTRODUCTION

This problem explores the Fashion MNIST dataset which contains 70000 gray-scale images in a 28 by 28-pixel grid, divided into ten different categories. The main objective of the problem is to observer whether a logistic regression model can accurately predict different clothing categories. Some of the key questions include but not limited to:

* Can the model achieve a good accuracy, i.e. more than 70% on the classification problem?
* How does L2 generalization affect the performance of the model?

# THE DATASET

The Fashion MNIST dataset consists of 70000 images divided into a training set of 60000 images and a testing set of 10000 images, with each image formatted as a 28 by 28 black and white pixel grid. The integers from 0 to 9 corresponds to the following label: 0 - T-shirt/top, 1 - Trouser, 2 – Pullover, 3 – Dress, 4 – Coat, 5 – Sandal, 6 – Shirt, 7 – Sneaker, 8 – Bag, 9 - Ankle boot. Some important characteristics of this data set include:

* The pixel values range from 0 to 255.
* The dataset is balance, meaning each category have the same number of samples.
* Visual similarities between some categories such as T-shirt/top and Shirt might lower the accuracy of the model.

# LOGISTIC REGRESSION

A logistic regression is a linear classification algorithm used to predict the probability of whether an input belongs to a specific class (Geeksforgeeks, 2017). There are certain advantages and disadvantages to this algorithm:

**Advantages:**

* Easy to implement, interpret and efficient.
* Can handle multiple class and make no assumption about classes (Geeksforgeeks, 2020).
* Can efficiently handle moderate dataset such as the Fashion MNIST.

**Disadvantages:**

* It has a linear boundary which may fail to recognize complex patterns.
* It assumes linearity between the dependent and independent variables.
* It cannot solve non-linear problems.

# DATA EXPLORATION

First, we import the necessary libraries for the problem:

import numpy as np

import matplotlib.pyplot as plt

from sklearn.linear\_model import LogisticRegression

from sklearn.metrics import classification\_report, confusion\_matrix

from sklearn.model\_selection import KFold, cross\_val\_score

from keras.datasets import fashion\_mnist

To load the dataset, we use the following snippet:

from keras.datasets import fashion\_mnist

# Loading the data

(X\_train, y\_train), (X\_test, y\_test) = fashion\_mnist.load\_data()

This returns the training and testing images – label pair and allow us to begin working on the dataset. To visualize some sample images, we use the following snippet:

plt.figure(figsize=(10, 4))

for i in range(10):

    plt.subplot(2, 5, i + 1)

    plt.imshow(X\_train[i], cmap='gray')

    plt.title(className[y\_train[i]])

    plt.axis('off')

This returns the first 10 sample images from the dataset. We can observe that the pixels weight ranges from 0 to 255; Classes are visually distinct, but some classes are hard to separate as seen in Figure 1.

Before building the model, we first normalize the data to fit with the requirements of logistic regression model:

X\_train\_flat =X\_train.reshape(X\_train.shape[0], -1).astype('float32') / 255.0

X\_test\_flat = X\_test.reshape(X\_test.shape[0], -1).astype('float32') / 255.0

We pass the following parameters into the regression model:

modelL2 = LogisticRegression (penalty='l2', max\_iter=500, C=1.0, random\_state=42)

For the mode, we used L2 regularization with 500 iterations. We use L2 regularization because it pushes the feature weights towards 0 and penalize large values. The parameter “c” controls the strength of regularization A higher “c” score means weaker regularization, while the inverse is true. Adjusting the “c” score might change the output of the program. Our target variables are y\_test and y\_train. Our feature variables concern the flattened and normalized 28 x 28 images. We can begin training the model and making predictions:

# Fitting and predicitng

modelL2.fit(X\_train\_flat, y\_train)

y\_pred = modelL2.predict(X\_test\_flat)

To measure the accuracy of the model, we use the following metrics – accuracy score, confusion matrix, classification report and K-Fold cross validation with 5 folds:

accuracy = modelL2.score(X\_test\_flat, y\_test)

print(f"Model accuracy: {accuracy:.4f}")

cm = confusion\_matrix(y\_test, y\_pred)

print("\nConfusion matrix: \n", cm)

print("\nClassification report: \n", classification\_report(y\_test, y\_pred))

cvScore = cross\_val\_score(modelL2, X\_test\_flat, y\_test, scoring="accuracy", n\_jobs=-1)

print(f"\nCross validations score on 5 fold: {cvScore.mean():.4f} +/- {cvScore.std():.4f}")

The accuracy of the model yields an 84.32% accurate prediction with a K-Fold score of 82.02. The confusion matrix in Figure 2 shows us the comparison between the model’s prediction output against the true label. For example, the label 0 – T-shirt/top have 806 accurate predictions but is often confused with label 6 – Shirt which reflects the similarity between these 2 classes. The classification report in Figure 3 has the following metrics:

* Precision: How many predictions is correct for a class
* Recall: How well the model identifies the items of a class
* F1-score: Harmonic mean of precision and recall

We can see the first 10 correct predictions and incorrect predictions in Figure 4 and Figure 5. A likely reason for the incorrect predictions observed seems to be the similarity between the different classes, such as ankle boots and sandals.

# CONCLUSION

The model achieved an accuracy of 84.28%, which is good for a simple linear model. The use of regularization has improved the K-Fold validation score by a small margin, meaning the model is more accurate with regularization. The incorrect predictions is a direct result of the disadvantage of the model, which is its inability to recognize complex patterns within a complicated dataset.

REFERENCES:

* GeeksforGeeks. “Logistic Regression in Machine Learning.” *GeeksforGeeks*, 9 May 2017, [www.geeksforgeeks.org/machine-learning/understanding-logistic-regression/](http://www.geeksforgeeks.org/machine-learning/understanding-logistic-regression/)
* GeeksforGeeks. “Advantages and Disadvantages of Logistic Regression.” GeeksforGeeks, 25 Aug. 2020, [www.geeksforgeeks.org/data-science/advantages-and-disadvantages-of-logistic-regression/](http://www.geeksforgeeks.org/data-science/advantages-and-disadvantages-of-logistic-regression/)

APPENDICES:

A group of different types of clothing

AI-generated content may be incorrect.

Figure 1: First 10 samples.

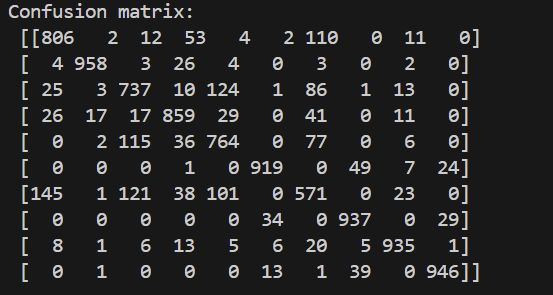


Figure 2: Confusion matrix.

A screenshot of a computer screen

AI-generated content may be incorrect.

Figure 3: Classification matrix.

A collage of different clothes

AI-generated content may be incorrect.

Figure 4: Correct prediction.

A collage of different clothing

AI-generated content may be incorrect.

Figure 5: Incorrect prediction.